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ON THE REINFORCED RELIABILITY OF FORWARD COLLISION WARNING SYSTEM WITH MACHINE LEARNING

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ABSTRACT

Researches on Advanced Driving Assistance System (ADAS) have been increased and ADAS has become a major field in automotive industry over the past few decades. One of the essential means comprising ADAS is Forward Collision Warning System (FCWS), which, from the safety point of view, should be designed to have high reliability and robustness against disturbance in noisy environment. FCWS in the market, however, still have vulnerability sensitive to the driving conditions and mounted sensors. We thus introduce an integrity monitoring approach on FCWS using the vehicle braking distance predictor which employs the neural network to predict the braking distance and aims to improve the reliability of the FCWS by preventing the accident by judging the abnormality of the system. The performance of the proposed vehicle braking distance predictor demonstrated the superiority in term of the prediction capability and robustness against the external noise compared with the existing mathematical braking distance model.

Keywords: advanced driving assistance system, forward collision warning system, machine learning, braking distance model

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1. INTRODUCTION

The 4th Industrial Revolution refers to the industrial changes that are expected to build virtual physical systems integrating real and virtual robot or artificial intelligence to automatically and intelligently control objects and it has been received wide attention over the past few years. The fields of the future industry of the 4th Industrial Revolution include autonomous driving technology that can recognize and judge the road situation by themselves without ant intervention by driver, Internet of Things (IoT), Artificial Intelligent (AI), Virtual Reality (VR), and so on.[7-8] Among these, autonomous driving is currently in the flow of rapid development, and one of the key features mounted on autonomous vehicles is the Advanced

Driver Assistance System (ADAS) which provides steering control to track lanes on the road, warning of collisions, speed control for smooth traffic flow and prevention of collision, etc.[3] In particular, the Forward Collision Warning System (FCWS) illustrated in Figure 1 is the most important and thus widely researched and developed field in recent years. The data used in the calculation of the FCWS are mega data and micro data, and the mega data is shared information, such as traffic volume and average speed, and the micro data are information such as the speed and the distance between cars collected by the individual vehicle sensor.[1]

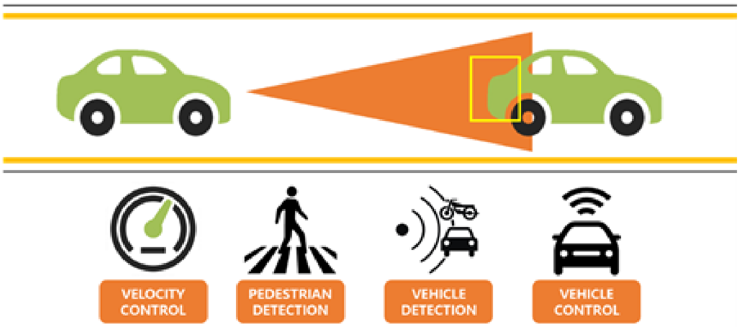


Figure 1 Illustration of FCWS

To obtain the micro data, it is possible to use various sensors such as radar, laser scanner, and video camera, but each sensor has its limitations.[2] The radar is excellent for accurate vehicle detection and over 100m long rage detection, but the accuracy of stopping and proximity detection is somewhat lower. In the case of a laser scanner, proximity vehicles and obstacles are outstanding, but the detection distance is short and making it difficult to detect long-distance vehicles and expensive. The detection performance of RGB camera has certain limitations due to the dependence of illumination and weather, and it is not able to calculate the exact distance to the object. Previous research aimed at designing braking distance models using different kinds of algorithms such as fractional energy rates and tire models.[5] However, based on standardized data, real-time FCWS may not be capable to be applied due to unexpected noise and individual vehicle conditions.

In this paper, we thus propose a vehicle braking distance prediction system for accident prevention and reinforcement by more stable detection of the limitation point and the possibility of forward collision inherent in the distance measurement function of FCWS which should be guaranteed in high stability and reliability. For braking distance prediction system implementation, Neural Networks (NN) can be a good candidate for consideration. NN is a family of machine learning algorithms known for its powerful features such as problem solving, optimization, and pattern classification of nonlinear data.[1] The existing FCWS is reinforced by the proposed Vehicle Braking Distance Predictor based on Neural Networks (VBDP-NN) which assists to determine the integrity of the FCWS by comparing of the predicted braking distance from VBDP-NN and the estimated braking distance from the existing mathematical Vehicle Braking Distance Model (VBDM). Through this, we aimed to prevent a forward collision accident caused by sensor malfunction and traveling noise and to improve the reliability of FCWS. After optimizing the proposed prediction system through strategic learning, we evaluated the predictive power and robustness against noise by comparing with the conventional VBDM, the proposed prediction system showed that the braking distance prediction error is greatly reduced and the performance is outstanding in the high-speed region where the robustness against the external environmental noise becomes important.

2. PRELIMINARIES ON NEURAL NETWORKS

Neural Networks (NN) that mathematically model human recognition processes and neural states have excellent performance in pattern analysis, optimization, and approximation.[6] Multi-Layer Perceptron (MLP) among many neural network structures is a great nonlinear problem-solving method and is applied to various fields such as signal processing, control, speech recognition, etc.[2] the structure of the NN with several hidden nodes in a single hidden layer and a single output (z)node is represented in Figure 2, and the connection weight $\boldsymbol{w}$ is adjusted through the activation function f by synthesizing the weight $\boldsymbol{w}$ with respect to the input value $\boldsymbol{x}_i$ $(1,2,\cdots$ L). Then the output values of the hidden layer and the output layer are represented by (1).

$$y_j = f\left(\sum_{i=1}^{L} w_{ji} x_i\right), z = f\left(\sum_{j=1}^{H} w_{zj} y_j\right) \quad \mathbf{1}$$

where w_{ji} is the weight connected between layers i and j and w_{zj} is the weight between layers j and z. $\boldsymbol{y}_j$ $(1,2,\cdots$ H) is the output from the previous input nodes, and z is an output from the previous hidden nodes. f is the sigmoid function formed as $f(\alpha) = 1/(1 - e^{-\alpha})$, an activation function, generally used to transform the linear saturation function into a differentiable form. The learning data of the neural networks are varied in size and range, so that normalization may be preceded for stable and fast learning in general. Neural Networks should find an optimal parameter, $\boldsymbol{w}$, that adjusts to minimize the error between the output value and the target value through learning.[1] The error function $\mathrm{E}(\boldsymbol{w})$ is minimized based on a back-propagation (BP) learning algorithm that can efficiently obtain the slope of the parameter in a least square sense. Based on the error function, the weight of the neural networks is then updated as (2).

$$\begin{aligned} w_{ji}(t+1) &= w_{ji}(t) + \delta \frac{\partial E}{\partial w_{ji}} \\ w_{zj}(t+1) &= w_{zj}(t) + \delta \frac{\partial E}{\partial w_{zj}} \end{aligned} \quad \mathbf{2}$$

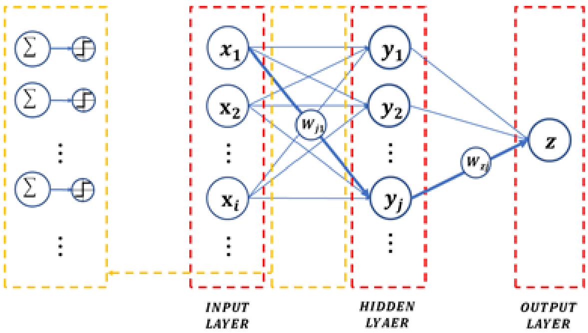


Figure 2 Internal structure of neural networks

3. REINFORCED FORWARD COLLISION WARNING SYSTEM

In general, the stopping distance of the vehicle consists of the braking distance and the reaction distance. The braking distance is defined as the distance traveled from the start of braking to the moment of stopping and the distance moved during the reaction time is called the reaction distance [9]; the time taken for the driver to start braking after stopping on the brakes after recognizing the danger is called the reaction time as illustrated in Figure 3.

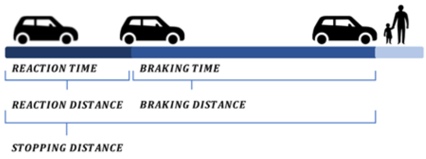


Figure 3 Illustration of stopping distance

The braking distance is primarily affected by the speed of the vehicle and the coefficient of friction between the tires and the road surface, and is expressed as (3).

$$l_f = \frac{V^2}{2g \times 3.6^2 \times \mu_b} \quad (3)$$

where g is an acceleration of gravity, $9.81\, {}^{m}/_{s^2}$, V is the speed of vehicle and μ_b is the coefficient of friction of the vehicle depending on the road surface condition. Coefficient of friction is maximum at dry and low speed due to the influence of speed and road surface, and minimum at wet and high speed.[4] In order to reinforce the existing FCWS, the Vehicle Braking Distance Predictor based on Neural Networks (VBDP-NN) is proposed as depicted in Figure 4 and is trained by the driving data set assuming that the reaction distance is immediate and the speed is limited to the range of $50{\sim}100\, {}^{km}/_{h}$ which is the standard of the motorway two-lane or more road. Also, taking into account the influence of various micro-driving environments that affect the friction coefficient, random values within the flat asphalt maximum speed criterion are added to the coefficient of friction to the slope value representing the slope of the road. The inputs to VBDP-NN are the speed of vehicle and the coefficient of friction of the vehicle, and the output of VBDP-NN is the braking distance.

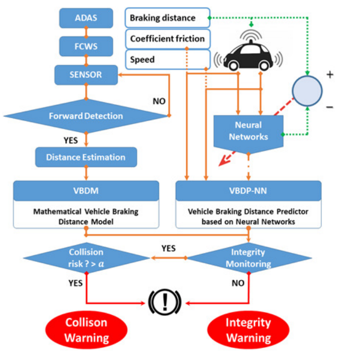
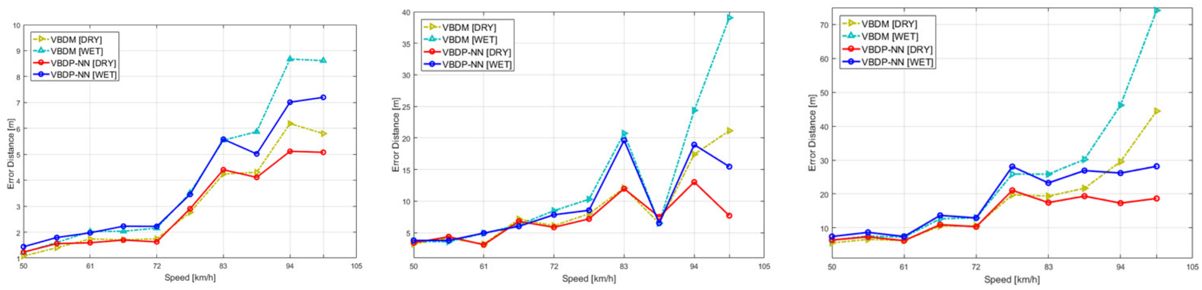


Figure 4 Block diagram of reinforced FCWS constructed by VBDP-NN

4. SIMULATION RESULTS

To evaluate the proposed VBDP-NN, the architecture of VBDP-NN was constructed through strategic learning. The learning rate was selected as 0.45 for dry road and 0.55 for wet road surface considering stability and reduction rate according to each road surface condition. The number of hidden nodes was chosen as 2 since the error did not decrease any longer regardless of the road surface condition at 2. Since the actual driving environment has a possibility of noise due to various situations and variables, which cannot be predicted, the VBDP-NN should be evaluated not only for simple numerical prediction but also for stability and robustness in a noisy environment. In order to verify this, test data including 5~25% random noise was generated and the stability and robustness of predicted values were evaluated through comparison of prediction error distances with VBDM, which is a standard model.



a b c

Figure 5 Performance comparisons of VBDP-NN and VBDM when (a) 5% noise (b) 15% noise (c) 25% noise

Table 1 Performance evaluation of VBDP-NN in terms of mean squared prediction error

	VBDP-NN		**VBDM**	
Speed $\left({km}/{h}\right)$ Noise %	50-85	85-100	50-85	85-100
DRY Condition				
5%	6.7	34	6.4	47
15%	56	185	57	458
25%	140	480	205	1622
WET Condition				
5%	10	73	11	102
15%	88	403	89	1092
25%	375	1045	378	4338

Table 1 shows the results of the performance evaluation according to the influence of the speed zone, the road surface condition and the noise, and the prediction error distance, when 5~25% of noise is included in the input data according to the road surface condition, is shown in figure 5 where the VBDP-NN shown similar predictive performance to VBDM with an approximate prediction error difference of less than 1% regardless of the road surface condition at a low speed of 85 ${km}/{h}$ or less. However, it showed 25%~ more difference predictability compared to VBDM. In particular, the robustness to noise of the VBDP-NN was increased as the level of noise interference increases. In the noisy environment of 15~25% and the high-speed section over 85 ${km}/{h}$, the prediction error from VBDP-NN was about 2.5~4 times lower than VBDM regardless of the road surface condition.

5. CONCLUDING REMARKS

In this paper, we proposed a reinforced forward collision warning system by predicting vehicle braking distance to prevent possible accidents when the forward collision warning system, which is used in the active control stage of the autonomous vehicle, is operated alone. The proposed reinforcement system detects the error by judging whether the system is abnormal due to the malfunction of the sensor and the noise by comparing the braking distances obtained from the existing forward collision warning system as well as the predicted value of the proposed VBDP-NN. In order to overcome the inaccuracy problem of the prediction from individual driving environment data, which is based on the standardized model, the proposed system adopts neural networks, which is a field of machine learning. After the optimal design of the neural networks, we compared with the existing vehicle braking distance model. As a result of comparing the performance with the existing braking distance model, the proposed VBDP-NN showed superior in the high-speed region where the stability and braking distance for noise that may occur in the actual driving environment are increased rapidly. The proposed vehicle braking distance prediction system has proved high predictive power and noise robustness through performance tests and can be expected to be used as a reinforcement system of actual FCWS.

6. ACKNOWLEDGEMENT

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